AI AND MBS – EMERGING TOOLS AND TECHNOLOGIES - HYPES VS REALITY

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Disclosures

Medtronic – Speaker/Proctor
BD – Speaker/Proctor
JnJ - Proctor
Levita - Consultant
Intuitive – training

ChatGPT used for presentation

the study of algorithms that give machines the ability to:

reason and perform cognitive functions such as -

problem solving, object and word recognition,

inference of world states,

and decision-making.

Bellman R. An introduction to artificial intelligence: Can computers think?: Thomson Course Technology, 1978.

4 subfields

1) Machine learning

2) Natural language processing

3) Artificial neural networks

4) Computer vision

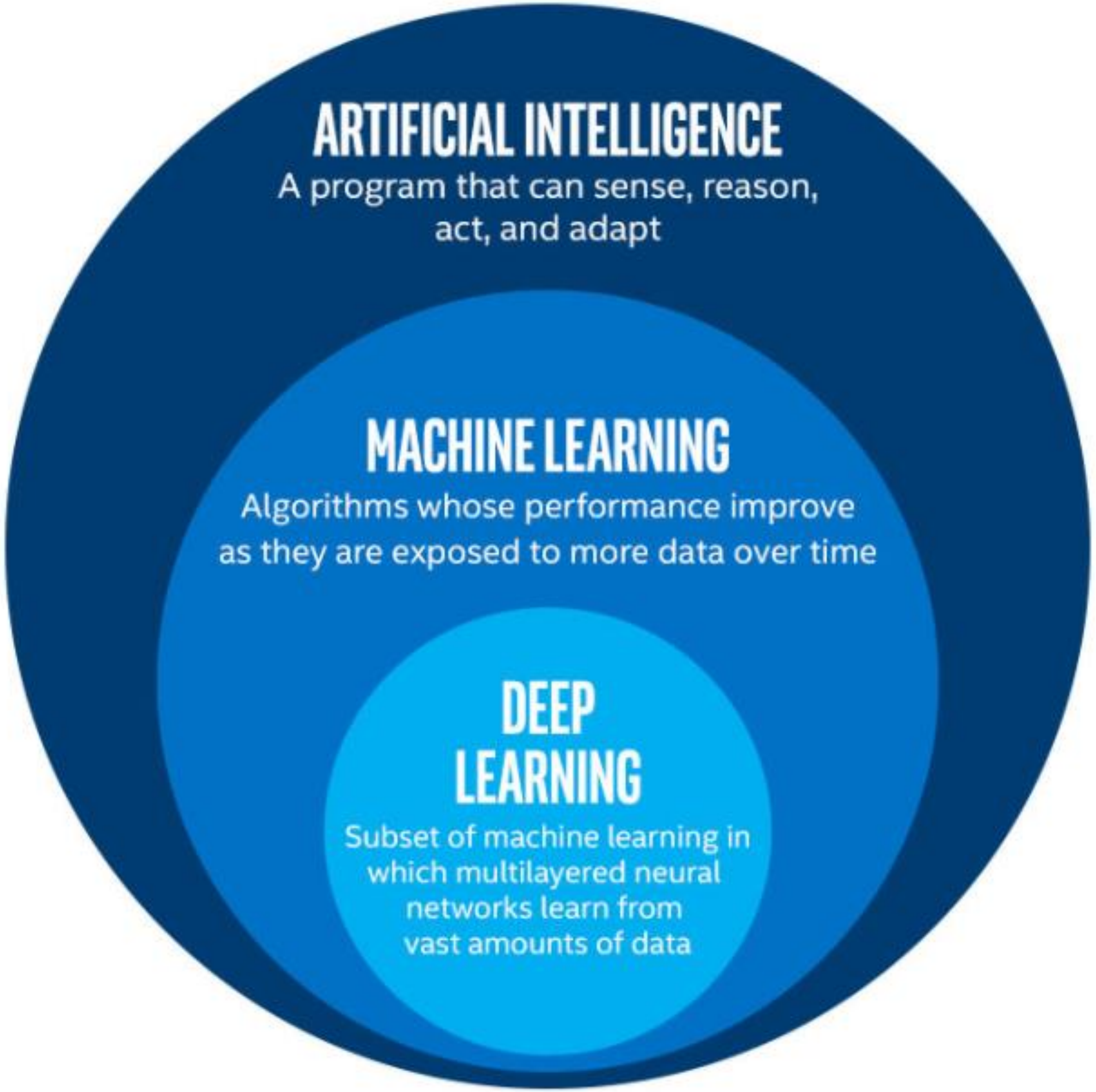


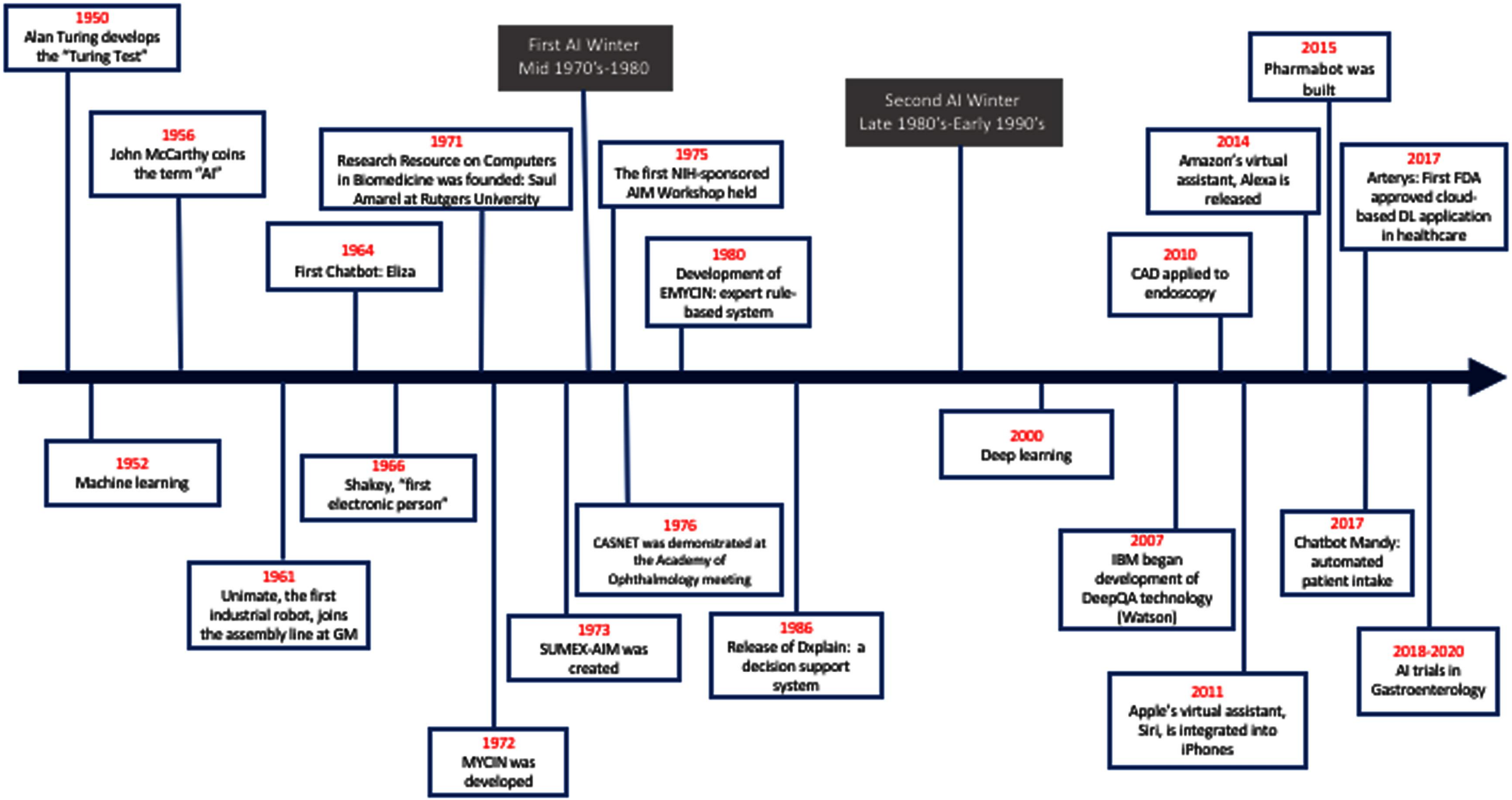
Table 1 Definitions of subclasses within AI

Subclass	Definition
Machine learning (ML)	ML involves computer science that is able to perform desired tasks based on input data. When provided with sufficient data, algorithms can recognize patterns in data and train the model to perform better. After completion of the final model, the algorithm can be applied to new unknown data [5]
Decision tree (DT)	Within a DT model, multiple factors are classified into tree branches. Based on the algorithm, these branches are divided into nodes, forming several tree pathways. In the end, this model tends to find the smallest tree that optimally fits the data [6]
Gradient boosting (GBM)	In GBM, weights are added to several factors after classification. Afterwards an assessment of weights occurs, in which weights are modified based on the difficulty to classify the factors. this process is repeated until a final optimal model is generated [7]
Random forest (RF)	RF involves the formation of multiple decision trees with specific values for predictors. This technique combines all decision trees in order to build an accurate model for predictions [8]
Support vector machine (SVM)	SVM models use mapped input data to discover the optimal boundary to separate several classes and values [9]
Deep learning	As a specific branch of machine learning, deep learning can recognize patterns within datasets by using multiple processing layers. Within each layer, weights are present for several factors within the model. After the training process, an optimal model is built to perform on new data [10]
Artificial neural networks (ANNs)	Similar to our brain system, data is passed through multiple processing layers within ANNs. Each layer contains weights in order to make decisions for the resulting output. By repeat of this process, this model can improve results and produce the most accurate model in the end [11]
Convolutional neural networks (CNNs)	CNNs are a specific type of neural networks, however no weights are used in the layers. Instead, multiple layers are functioning as filters to register patterns or regions of images [12]
Radiomics	A radiomics model analyzes images in order to retrieve specific texture features that are registered as a 0 or 1. By detecting these features, various pathologies could be recognized [13]

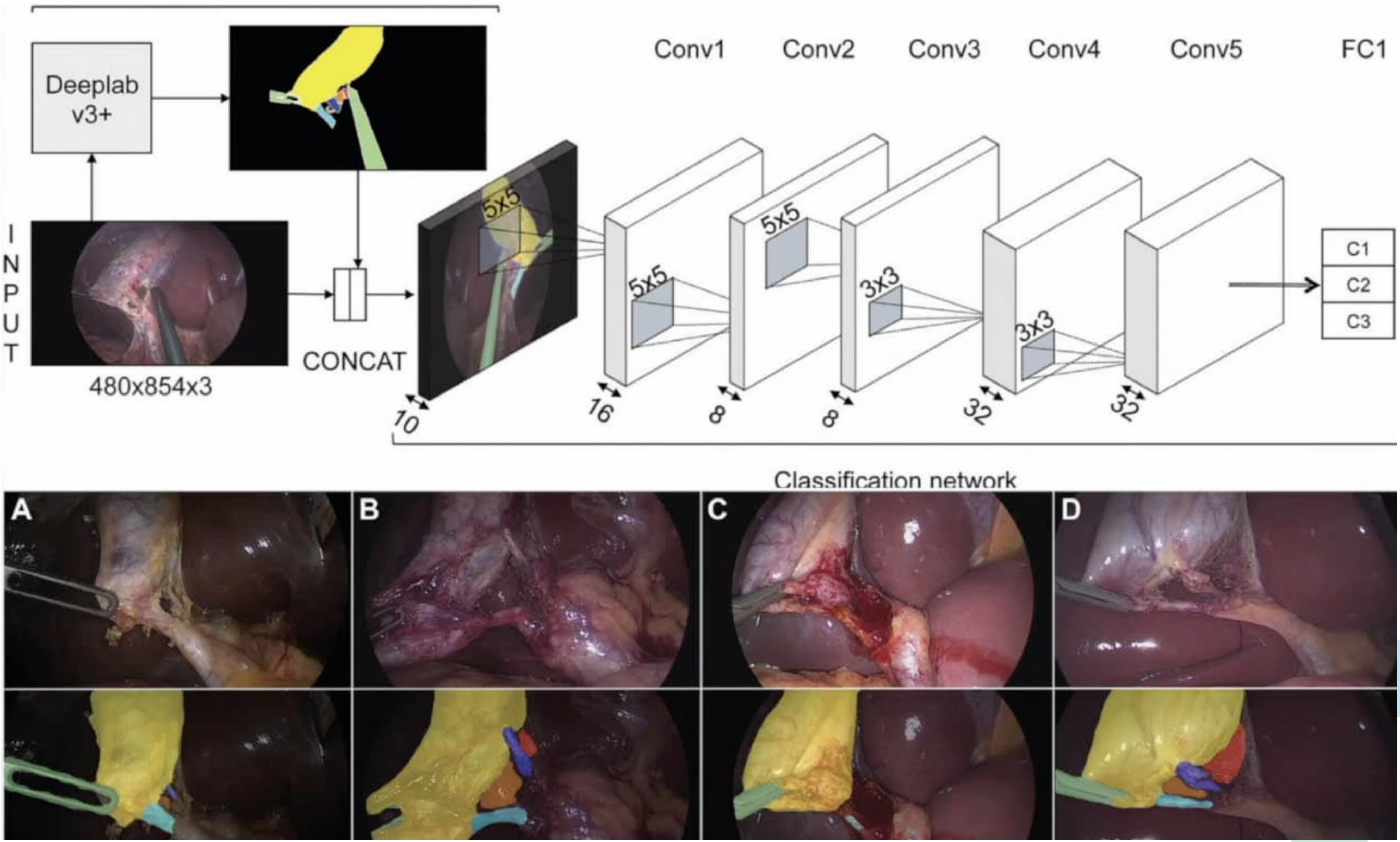
Abbreviations: ML, machine learning; *DT*, decision tree; *GBM*, gradient boosting machine; *RF*, random forest; *SVM*, support vector machine; *ANN*, artificial neural networks; *CNN*, convolutional neural networks

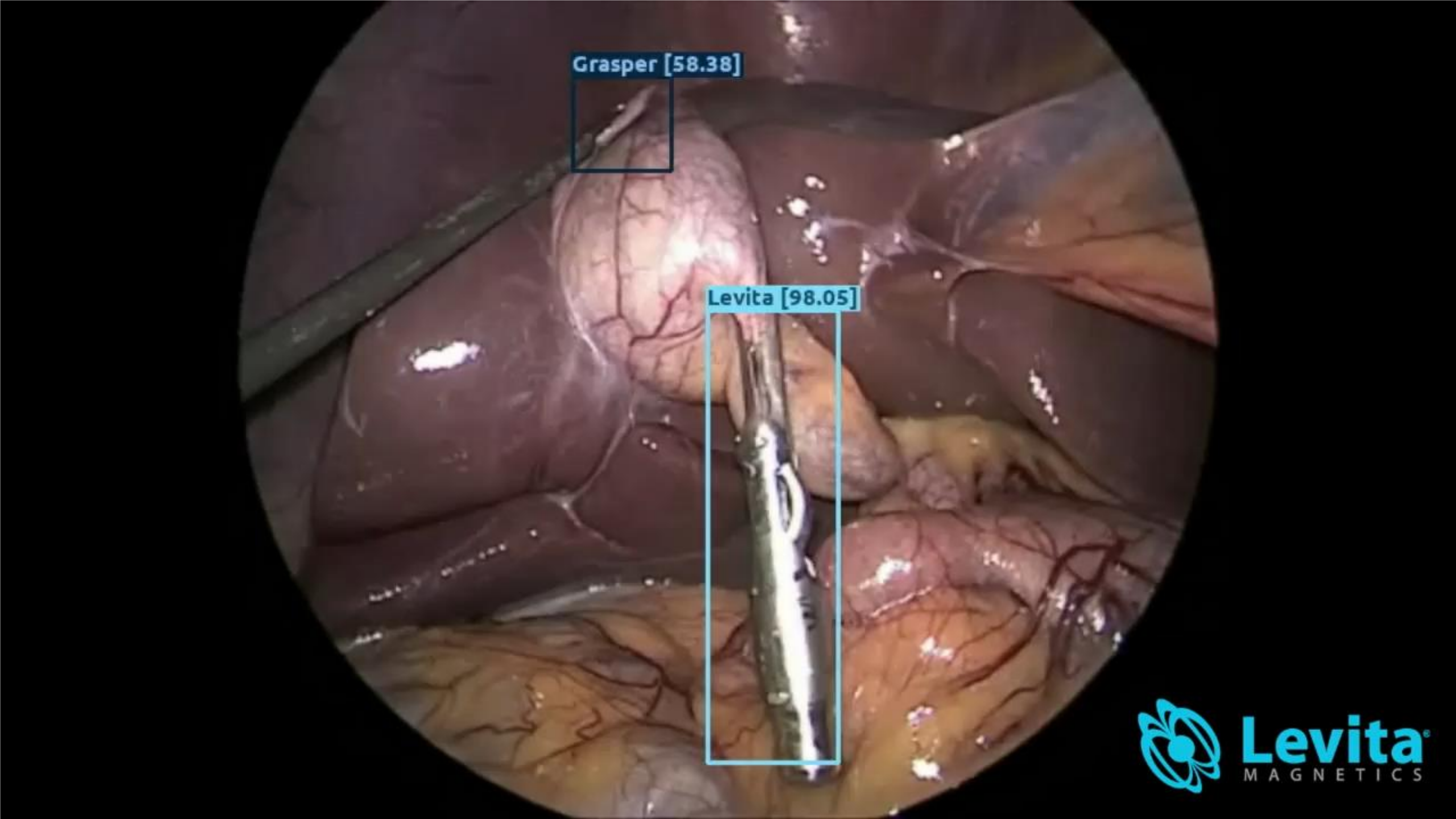
Exploring the Historical Journey of Artificial Intelligence

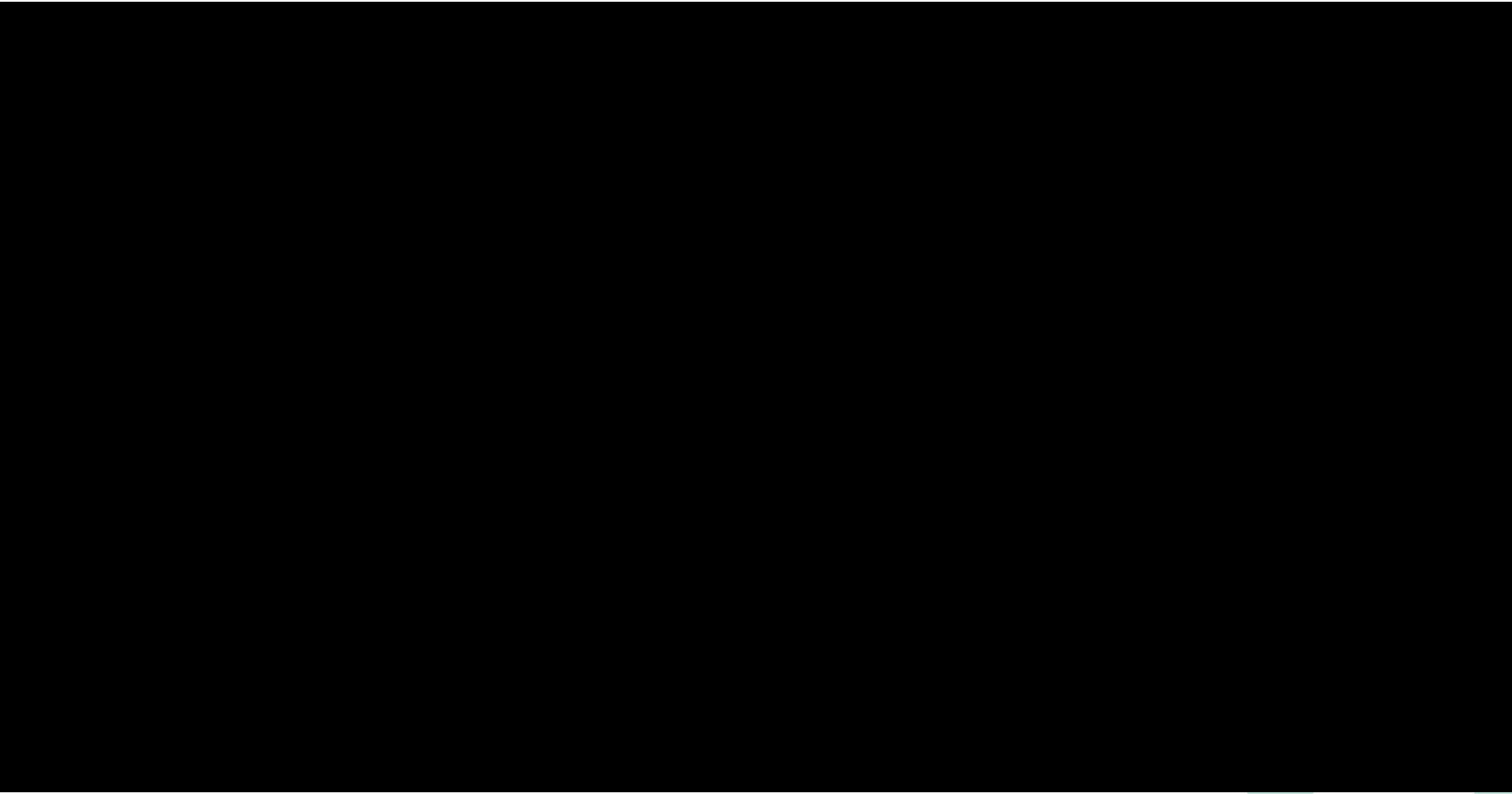
1942	1950	1955	1964	1995	1997	1998	2008	2011	2020
1	2	3	4	5	6	7	8	9	10
Enigma broken with AI	Test for machine intelligence by Alan Turing	The father of AI – John McArthy	The first chatbot – Eliza	The chatbot ALICE	Man vs Machine – DeepBlue beats chess legend	The emotionally equipped robot – Kismet	Voice recognition feature	The Q/A computer system – IBM Watson	A revolutionary tool for automated conversations – GPT models



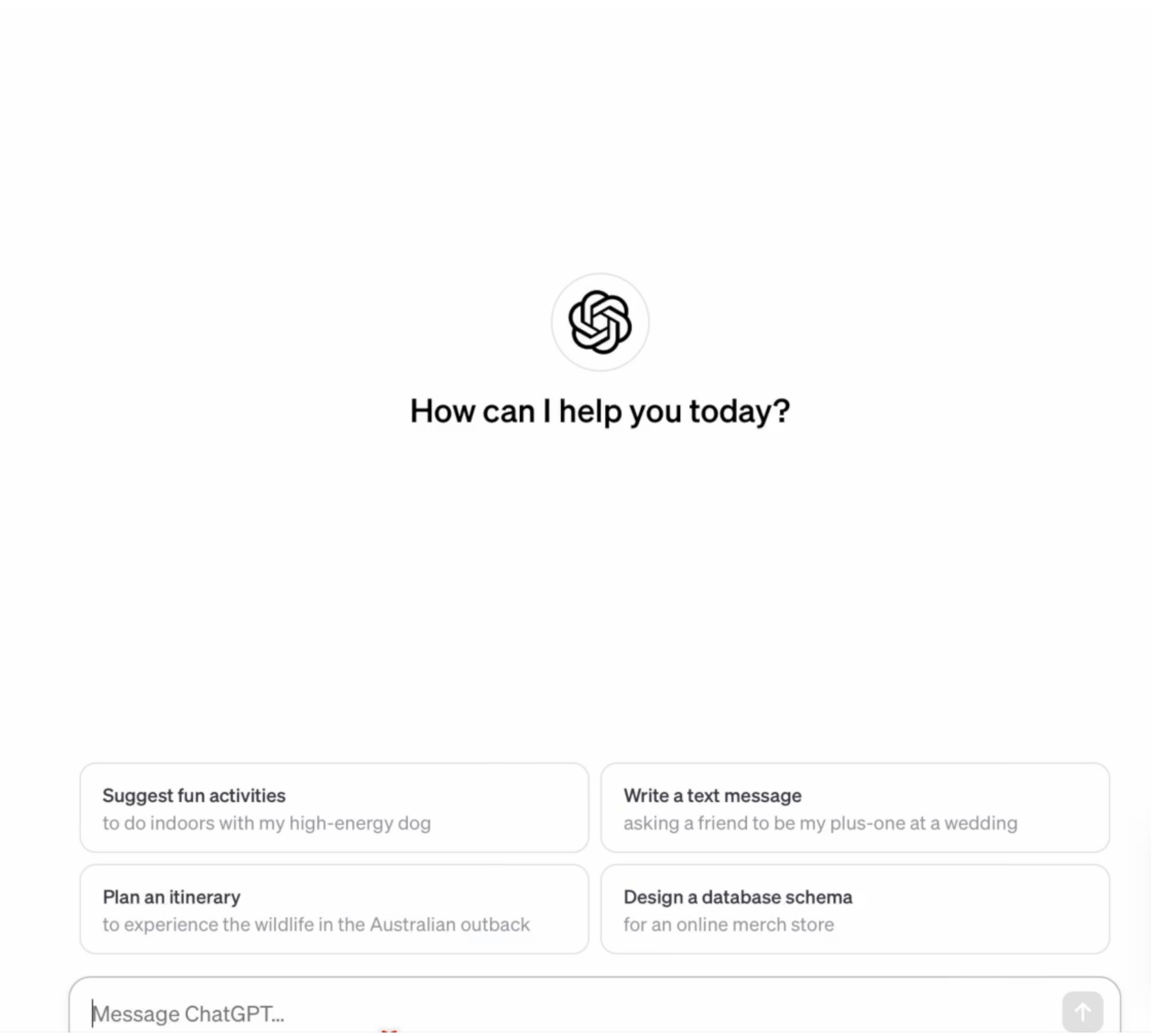
1950
Alan Turing develops the "Turing Test"
1952
Machine learning
1956
John McCarthy coins the term "AI"
1961
Unimate, the first industrial robot, joins the assembly line at GM
1964
First Chatbot: Eliza
1966
Shakey, "first electronic person"
1971
Research Resource on Computers in Biomedicine was founded: Saul Amarel at Rutgers University
1972
MYCIN was developed
1973
SUMEX-AIM was created
First AI Winter
Mid 1970's-1980
1975
The first NIH-sponsored AIM Workshop held
1976
CASNET was demonstrated at the Academy of Ophthalmology meeting
1980
Development of EMYCIN: expert rule-based system
1986
Release of Dxplain: a decision support system
Second AI Winter
Late 1980's-Early 1990's
2000
Deep learning
2007
IBM began development of DeepQA technology (Watson)
2010
CAD applied to endoscopy
2011
Apple's virtual assistant, Siri, is integrated into iPhones
2014
Amazon's virtual assistant, Alexa is released
2015
Pharmabot was built
2017
Arterys: First FDA approved cloud-based DL application in healthcare
2017
Chatbot Mandy: automated patient intake
2018-2020
AI trials in Gastroenterology


Deeplab v3+
Conv1
Conv2
Conv3
Conv4
Conv5
FC1
INPUT
480x854x3
CONCAT
5x5
5x5
5x5
3x3
3x3
10
16
8
8
32
32
C1
C2
C3
Classification network
A
B
C
D


Grasper [58.38]
Levita [98.05]
Levita
MAGNETICS



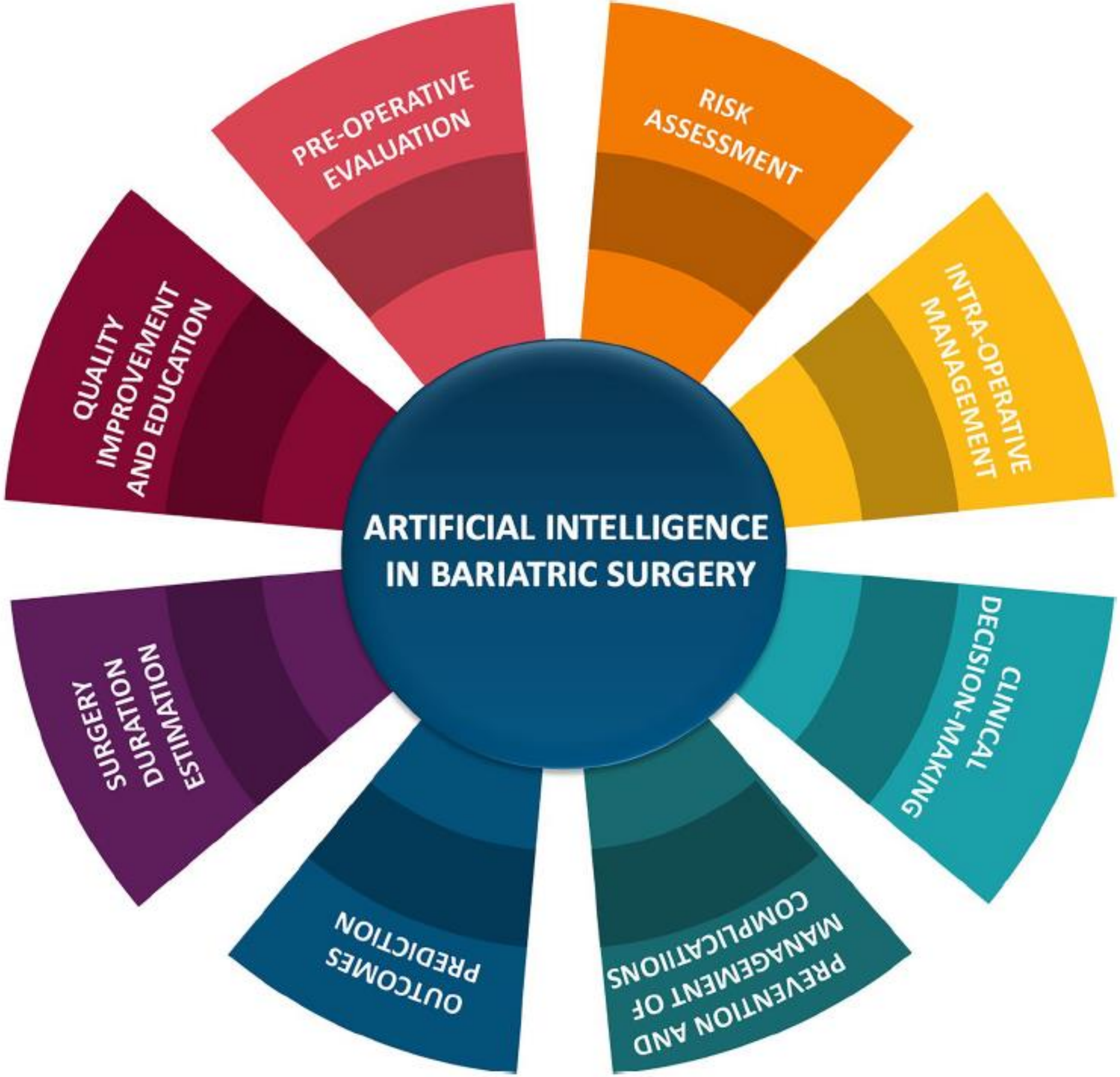

The Collective Surgical Consciousness
AI
Hashimoto, Rosman et al. (2018) *Ann Surg.* 268(1)



1) Diagnostic Support
2) Surgical Planning
3) Robot Assisted Surgery
4) Predictive Analytics
5) Work Flow Optimization
6) Intraoperative Decisions Support
7) Rehabilitation and Recovery monitorin
8) Data Security and Privacy


PAAS
DAPPS
AR
ALGORITHM
INDUSTRY 4.0
ROBOTICS
WEARABLES
BLOCKCHAIN
MACHINE
LEARNING
PREDICTIVE ANALYSIS
DATA MINING
VOICE RECOGNITION
ARTIFICIAL INTELLIGENCE
SAAS
NET NEUTRALITY
IOT
BIOMETRICS
DEEP LEARNING
QUANTUM COMPUTING
VR
CHATBOTS
NEURAL
BIG DATA
SMART CITIES
ZETTABYTE
MICROSERVICES
CLOUD
5G
LI-FI

- Patient Centered
- Clinician Centered
- System Centered



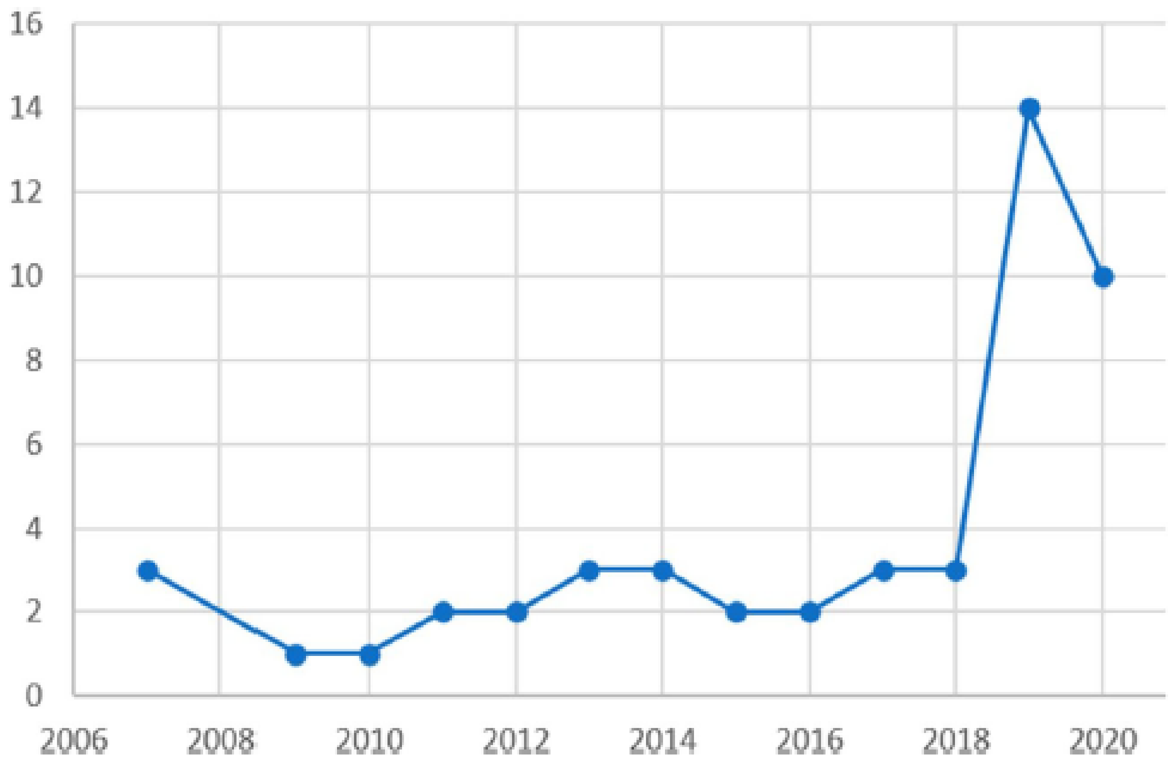
AI in Bariatric Surgery

Obesity Surgery
https://doi.org/10.1007/s11695-021-05548-x

REVIEW

A Scoping Review of Artificial Intelligence and Machine Learning in Bariatric and Metabolic Surgery: Current Status and Future Perspectives

Athanasios G. Pantelis[1] • Georgios K. Stravodimos[1] • Dimitris P. Lapatsanis[1]



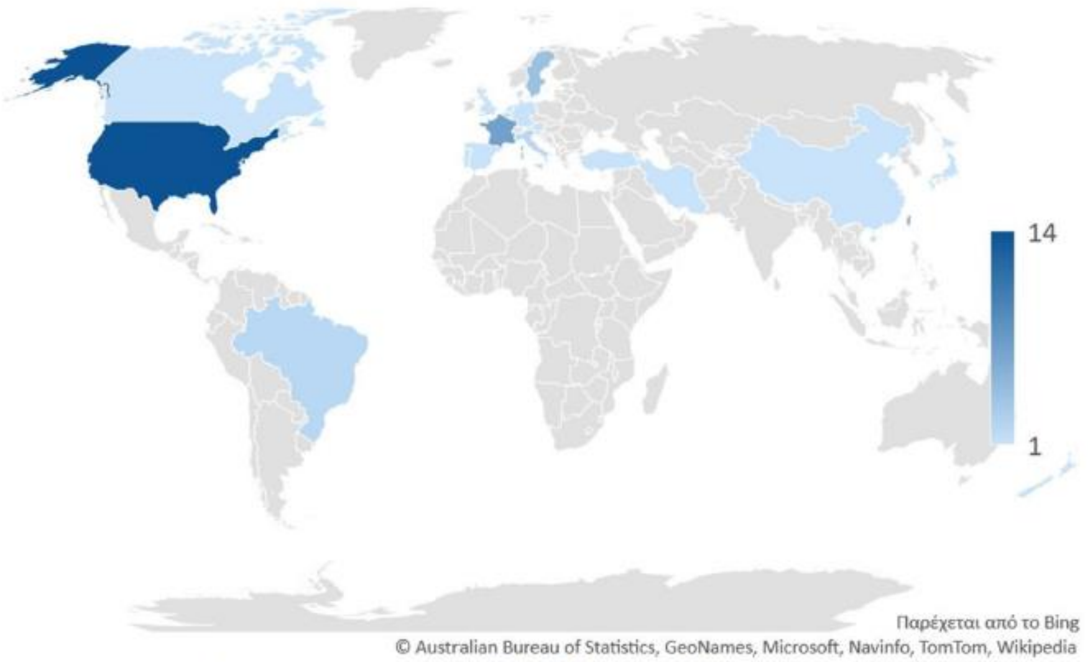


Fig. 2 Geographical distribution of the studies included in the review. The darker the hue, the higher the number of studies from this particular country

Pantelia AG, et al. Obesity Surgery 2022 https://doi.org/10.1007/s11695-021-05548-x

AI in Bariatric Surgery

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REVIEW

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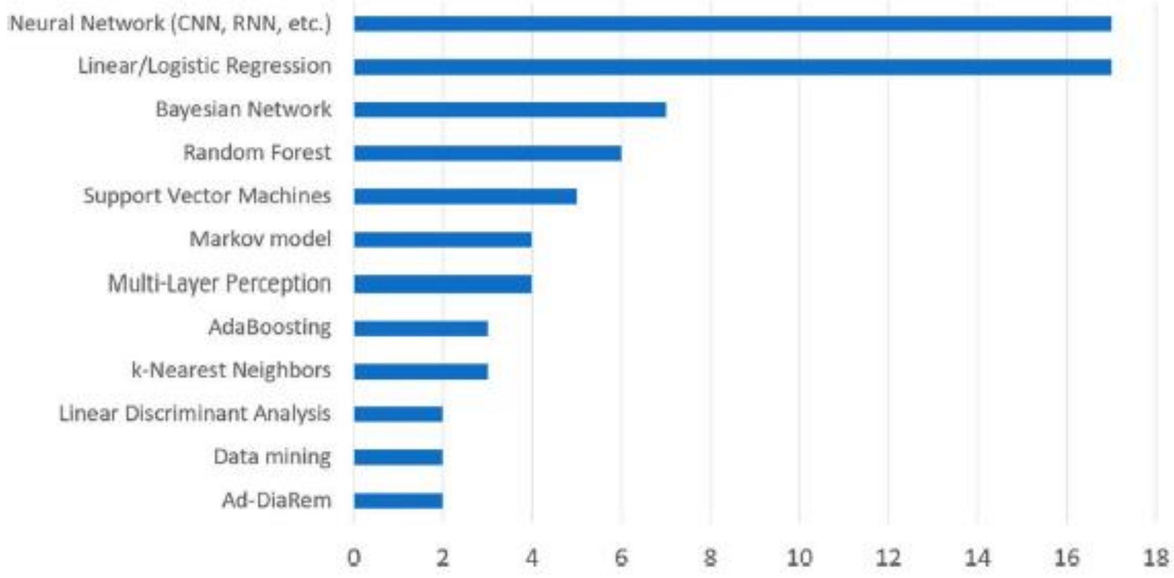
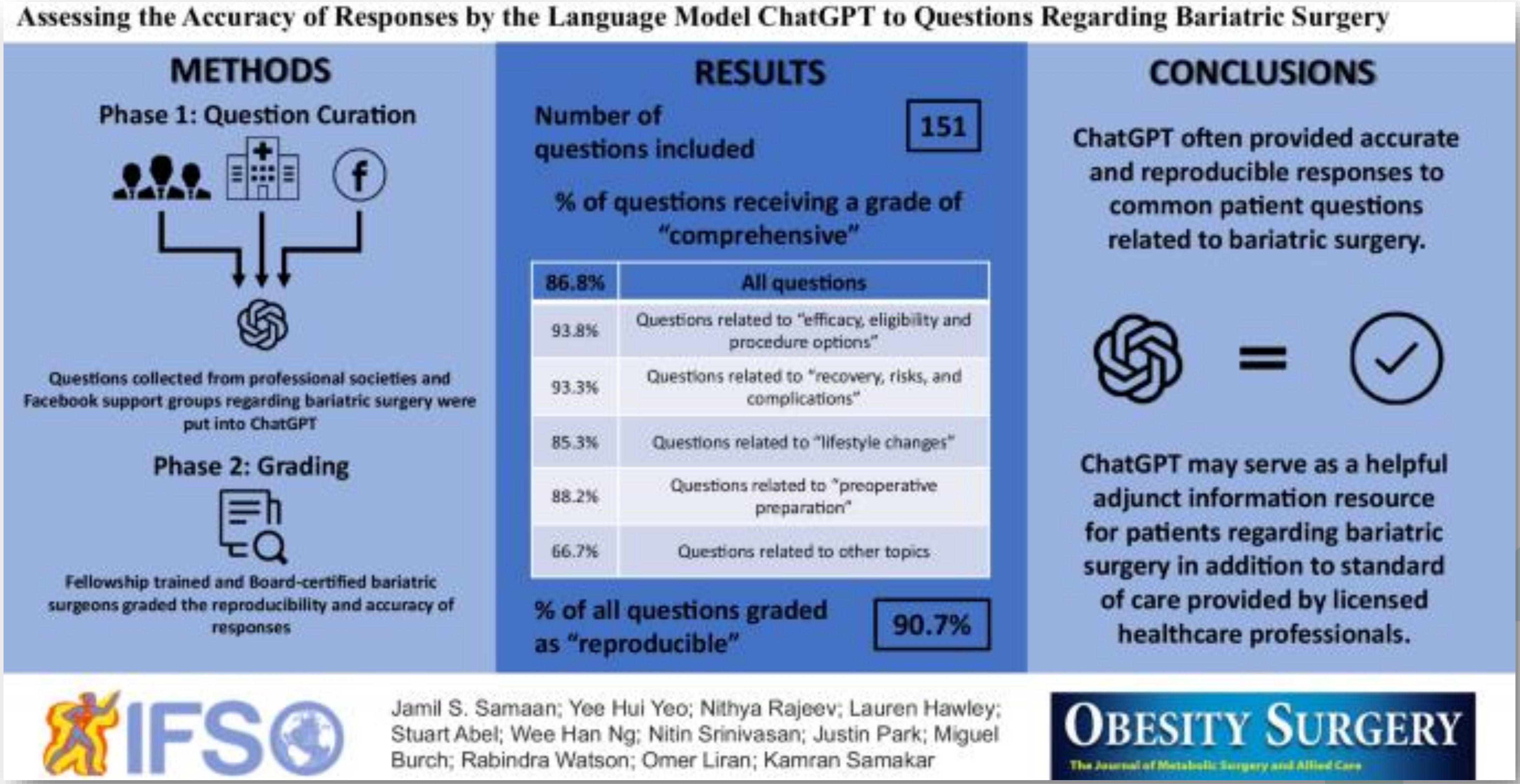
Category	Subject	No. of studies [reference number]
Basic science	The study investigates a molecular/genomic/proteomic effect in people living with obesity who have undergone BMS with the aid of an ML/DL algorithm	**4** [9, 12, 28, 44]
Safety (complications)	The study investigates the accuracy of ML/DL algorithms to predict complications following BMS	**13** [10, 13, 14, 27, 32 33, 38-40, 47, 49-51]
Effectiveness	The study investigates the accuracy of ML/DL algorithms to predict weigh loss following BMS	**11** [11, 18, 29, 31, 33, 35-37, 48, 54, 55]
Comorbidities	The study investigates the accuracy of ML/DL algorithms to predict the impact of BMS on comorbidities (NAFLD, T2DM, HTN, OSA, etc.)	**12** [7, 8, 15, 22-22, 34, 42, 45, 46, 53]
Quality of life	The study investigates the accuracy of ML/DL algorithms to predict the impact of BMS QoL	**2** [52, 53]
Operative	The study investigates the analytic effects of ML/DL algorithms on various intraoperative aspects (i.e., assessment of technique through intraoperative video)	**5** [16, 20, 21, 43, 44]
Cost	The study uses an algorithm to make cost-effectiveness predictions	**4** [17, 19, 28, 30]



Pantelia AG, et al. Obesity Surgery 2022 https://doi.org/10.1007/s11695-021-05548-x

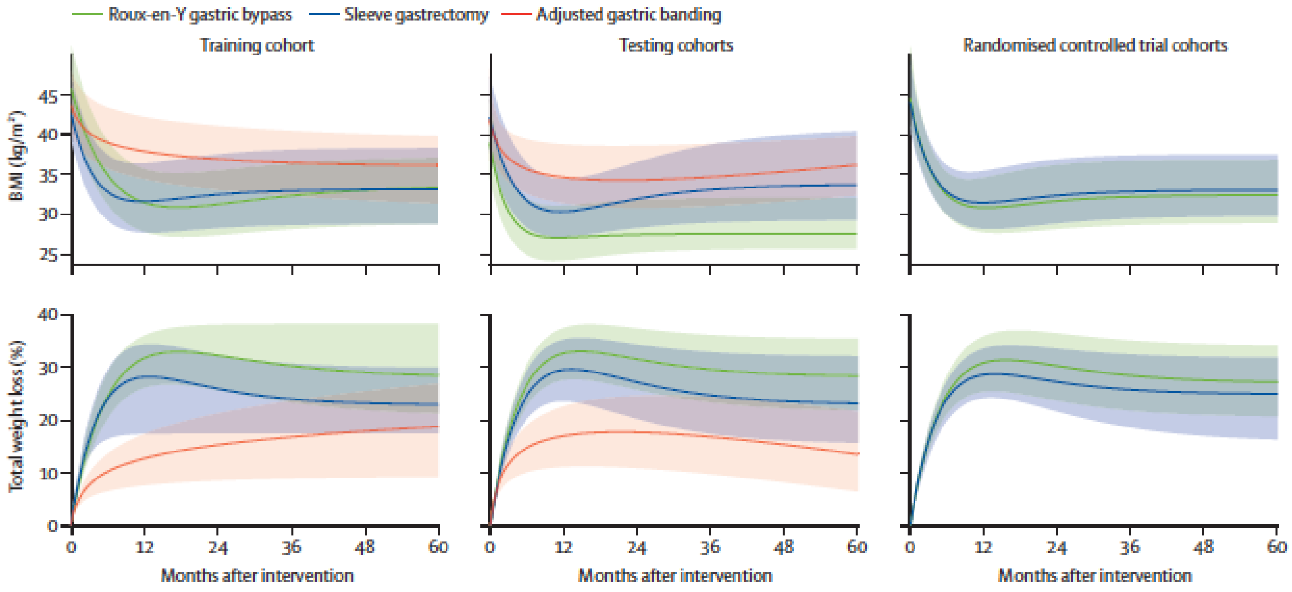
AI, Patient Education

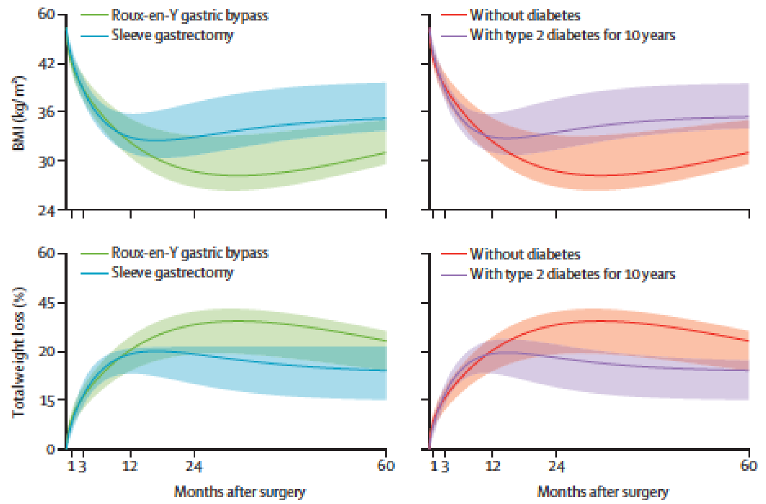


AI, Weight Loss

Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort SOPHIA study

Patrick Saux*, Pierre Bauvin*, Violeta Raverdy, Julien Teigny, Hélène Verkindt, Tomy Soumphonphakdy, Maxence Debert, Anne Jacobs, Daan Jacobs, Valerie Monpellier, Phong Ching Lee, Chin Hong Lim, Johanna C Andersson-Assarsson, Lena Carlsson, Per-Arne Svensson, Florence Galtier, Guelareh Dezfoulian, Mihaela Moldovanu, Severine Andrieux, Julien Couster, Marie Lepage, Erminia Lembo, Ornella Verrastro, Maud Robert, Paulina Salminen, Geltrude Mingrone, Ralph Peterli, Ricardo V Cohen, Carlos Zerrweck, David Nocca, Carel W Le Roux, Robert Caiazzo, Philippe Preux, François Pattou





	BMI difference* in kg/m² (SD)			RMSE† in kg/m² (95% CI)‡			Normalised RMSE† in percentage of BMI (95% CI)‡		
	Month 12	Month 24	Month 60	Month 12	Month 24	Month 60	Month 12	Month 24	Month 60
Roux-en-Y gastric bypass	–0·0 (3·2)	–0·4 (3·9)	–0·3 (4·5)	3·2 (3·2–3·3)	3·9 (3·9–4·0)	4·5 (4·3–4·6)	11·0 (10·8–11·2)	13·5 (13·2–13·8)	14·6 (14·1–15·0)
Sleeve gastrectomy	–0·4 (4·3)	1·0 (4·8)	0·9 (5·6)	4·3 (4·2–4·5)	4·9 (4·7–5·2)	5·7 (5·4–6·0)	13·2 (12·7–13·8)	14·9 (14·2–15·6)	16·2 (15·3–17·2)
Adjusted gastric banding	1·7 (3·9)	0·7 (4·1)	–2·8 (4·3)	4·7 (4·2–5·4)	4·7 (4·1–5·3)	6·0 (5·4–6·7)	13·6 (11·9–15·3)	13·6 (12·0–15·3)	16·6 (14·9–18·4)

RMSE=root mean squared error. *BMI difference is difference between predicted and observed BMI (negative means predicted was lower than observed). †RMSE is the measure of prediction bias and standard deviation; the lower, the more accurate. ‡95% CI are bias-corrected and accelerated bootstrap, n=10 000 replications.

Table 3: Comparison of predicted outcomes by operation in validation cohorts

AI, DM

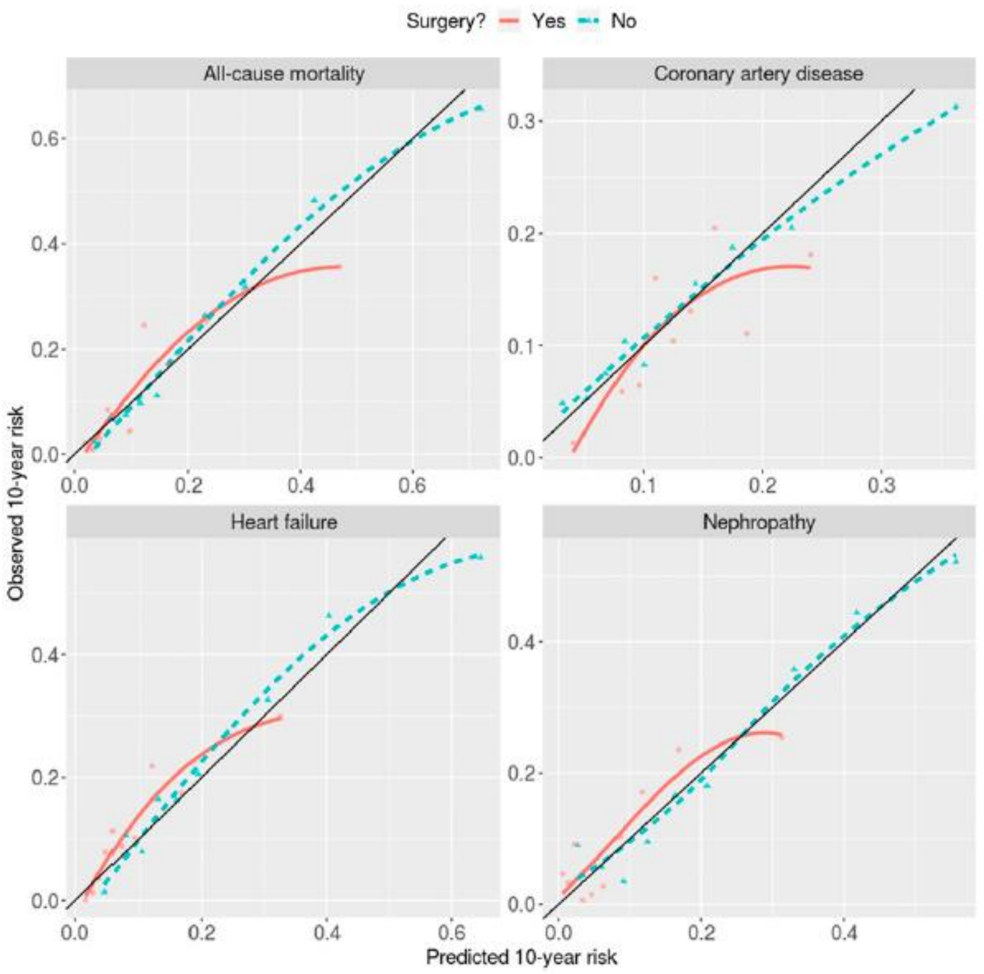


Figure 1—Calibration of cross-validated 10-year risks for each outcome, stratified by treatment group. Cross-validated risks were binned into 10 subgroups, and each subgroup's average risk was plotted against the observed cumulative incidence of the subgroup (Kaplan-Meier for all-cause mortality). Local regression smoothers were then drawn through the points. The closer the points lie along the 45° line, the better the calibration.

Predicting 10-Year Risk of End-Organ Complications of Type 2 Diabetes With and Without Metabolic Surgery: A Machine Learning Approach

Ali Aminian,[1] Alexander Zajichek,[2] David E. Arterburn,[3] Kathy E. Wolski,[4] Stacy A. Brethauer,[1,5] Philip R. Schauer,[1,6] Steven E. Nissen,[4] and Michael W. Kattan[2]

Diabetes Care 2020;43:852–859 | https://doi.org/10.2337/dc19-2057

Index of Prediction Accuracy

Table 2—Performance of IDC Risk Scores on training data set and comparison with the RECODe models for nonsurgical patients

		Performance of IDC Risk Scores			Model comparison*			
					IDC		RECODe	
Outcome	Group	Model	IPA	AUC	IPA	AUC	IPA	AUC
All-cause mortality	Metabolic surgery	Regression	0.13	0.79	—	—	—	—
All-cause mortality	Usual care	Regression	0.24	0.81	0.20	0.78	0.12	0.76
Coronary artery events	Metabolic surgery	Random forest	0.03	0.66	—	—	—	—
Coronary artery events	Usual care	Regression	0.04	0.67	—	—	—	—
Heart failure	Metabolic surgery	Regression	0.05	0.73	—	—	—	—
Heart failure	Usual care	Regression	0.14	0.75	0.15	0.75	0.004	0.73
Nephropathy	Metabolic surgery	Regression	0.07	0.73	—	—	—	—
Nephropathy	Usual care	Random forest	0.14	0.76	0.18	0.77	−0.19	0.60

*Assessment of nonsurgical models on 12,816 patients at the Cleveland Clinic who were not included in the training data set was performed by direct comparison of IDC Risk Scores and the RECODe formulas (18,19). The IDC Risk Scores outperformed RECODe for all three examined outcomes (mortality, heart failure, and nephropathy) in terms of IPA, AUC, and calibration.

AI, DM

Predicting 10-Year Risk of End-Organ Complications of Type 2 Diabetes With and Without Metabolic Surgery: A Machine Learning Approach

Ali Aminian,[1] Alexander Zajichek,[2] David E. Arterburn,[3] Kathy E. Wolski,[4] Stacy A. Brethauer,[1,5] Philip R. Schauer,[1,6] Steven E. Nissen,[4] and Michael W. Kattan[2]

Diabetes Care 2020;43:852–859 | https://doi.org/10.2337/dc19-2057

- Female 50 YO
  - BMI 35 kg/m2,
  - HbA1c 7.8%,
  - BO 130/70 mmHg
  - Crs 1 mg/dL
  - Tgl 150 mg/dL
  - No Hx of complications micro/macro
  - Insulin and Statins

Risk of Mortality (%)	10 years	QxM
All causes	10.9	5.6
Coronary Disease	7.7	5.6
Heart failure	12.2	4.2
Diabetic nephropaty	24.8	8

Aminian A et al. Obesity Surgery 2022 32:2772-83

AI, Procedure Selection

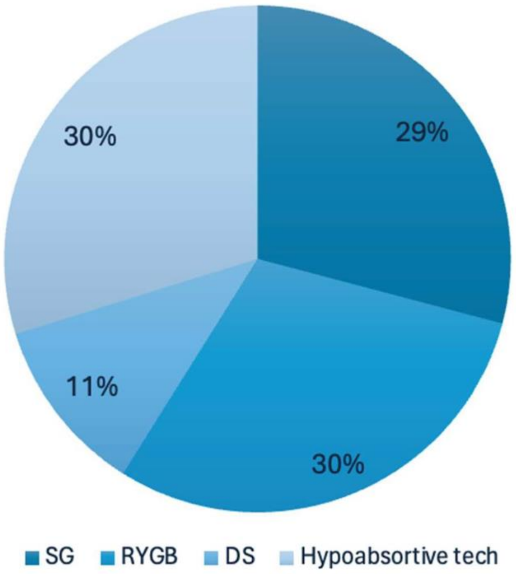
- OpenAI's GPT-4 to analyze:
  - Demographics
  - Medical history
  - BMI
  - Recommend the most suitable surgical technique
- Compared to actual surgery:
  - 34.2% match rate


Obesity Surgery (2025) 35:19–24
https://doi.org/10.1007/s11695-024-07279-1

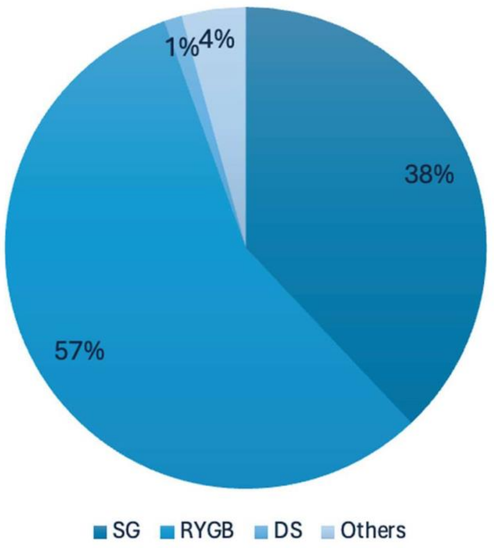
ORIGINAL CONTRIBUTIONS

Evaluation of the Impact of ChatGPT on the Selection of Surgical Technique in Bariatric Surgery

Ruth Lopez-Gonzalez[1] · Sergi Sanchez-Cordero[1] · Jordi Pujol-Gebelli[1] · Jordi Castellvi[1]



Graph 1 Distribution according to the surgical technique performed



Graph 2 Distribution according to the technique suggested by Chat-GPT4

AI, Complications

Surgical Endoscopy (2024) 38:319–326
https://doi.org/10.1007/s00464-023-10429-8

2023 SAGES ORAL

Machine learning prediction of major adverse cardiac events after elective bariatric surgery

Gustavo Romero-Velez[1] · Jerry Dang[2] · Juan S. Barajas-Gamboa[3] · Terrence Lee-St John[3] · Andrew T. Strong[2] · Salvador Navarrete[2] · Ricard Corcelles[2] · John Rodriguez[3] · Maan Fares[4] · Matthew Kroh[2]

NN es ~ 11.8% más sensible y tiene un VPP ~ 11.3% mayor que la RL y XGBoost.

Table 2 Model performance

Model	AUC			Predicted status		Specificity (%)	Sensitivity (%)	PPV (%)	NPV (%)
				No MACE	MACE				
Logistic regression	0.790	Actual status	No MACE	358,525	18,870	95.0	31.7	0.80	99.9
			MACE	328	152				
Neural network	0.798	Actual status	No MACE	358,525	18,870	95.0	35.4	0.89	99.9
			MACE	310	170				
XGBoost	0.787	Actual status	No MACE	358,525	18,870	95.0	31.7	0.80	99.9
			MACE	328	152				

AUC area under the curve, *PPV* positive predictive value, *NPV* negative predictive value

Romero-Velez G et al. Surg Endosc 2024 https://doi.org/10.1007/s00464-023-10429-8

AI, Complications

Surgical Endoscopy (2021) 35:182–191
https://doi.org/10.1007/s00464-020-07378-x

Development and validation of machine learning models to predict gastrointestinal leak and venous thromboembolism after weight loss surgery: an analysis of the MBSAQIP database

Jacob Nudel[1,2] · Andrew M. Bishara[3,4] · Susanna W. L. de Geus[1] · Prasad Patil[5] · Jayakanth Srinivasan[2] · Donald T. Hess[1] · Jonathan Woodson[2]

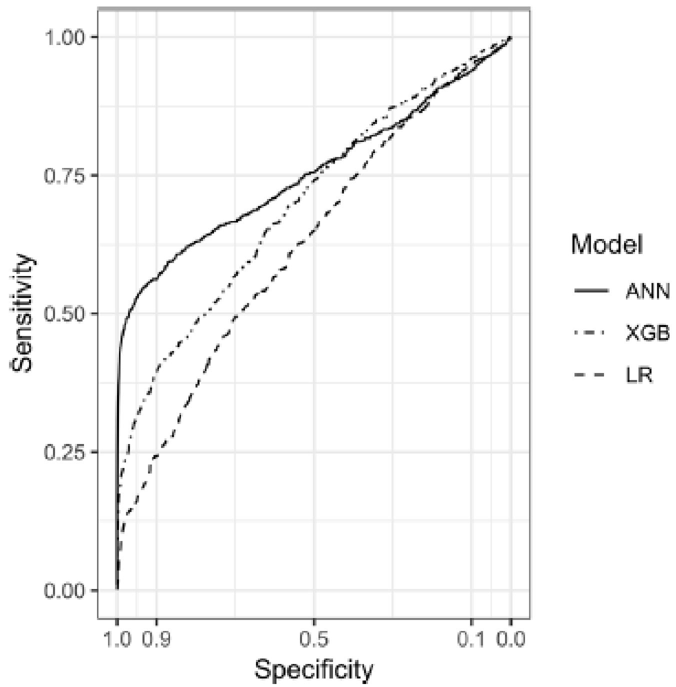


Fig. 1 Receiver Operating Characteristic Curves for Predicting Gastrointestinal Leak. *ANN* artificial neural network, *XGB* gradient boosting machine, *LR* logistic regression

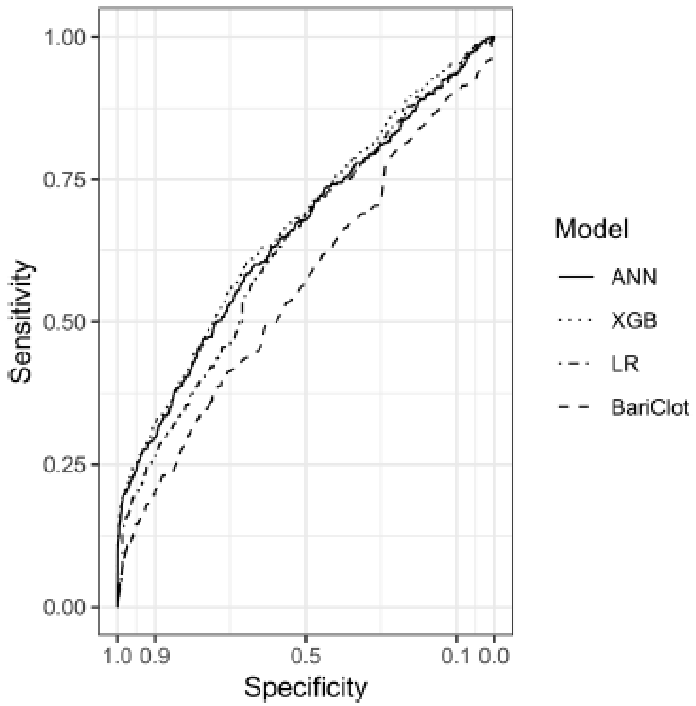
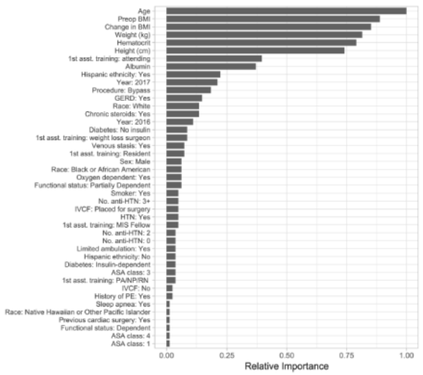
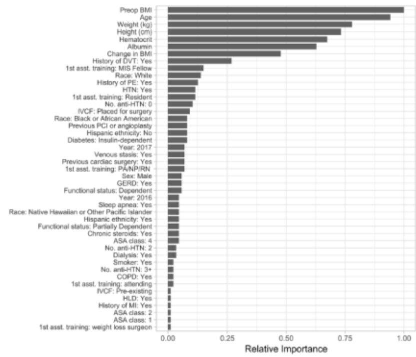


Fig. 2 Receiver operating characteristic curves for predicting venous thromboembolism. *ANN* artificial neural network, *XGB* gradient boosting machine, *LR* logistic regression

Table 2 Performance characteristics of the artificial neural network (ANN), gradient boosting machine (XGB), and logistic regression (LR) models for predicting gastrointestinal leak at the 97.5% specificity threshold

	Sensitivity, median (95% CI)	Specificity, median (95% CI)	PPV, median (95% CI)
Model			
ANN	0.493 (0.458–0.529)	0.975 (0.974–0.976	0.122 (0.114–0.131)
XGB	0.24 (0.209–0.270)	0.975 (0.974–0.976)	0.063 (0.056–0.071)
LR	0.134 (0.111–0.159)	0.975 (0.974–0.976)	0.037 (0.030–0.043)





Nudel J et al. Surg Endosc 2021 https://doi.org/10.1007/s00464-020-07378-x

Research

Obesity Pillars 6 (2023) 100065

Contents lists available at ScienceDirect

Obesity Pillars

journal homepage: www.journals.elsevier.com/obesity-pillars

Review

Artificial intelligence and obesity management: An Obesity Medicine Association (OMA) Clinical Practice Statement (CPS) 2023

Harold Edward Bays[a,*], Angela Fitch[b], Suzanne Cuda[c], Sylvia Gonsahn-Bollie[d], Elario Rickey[e], Joan Hablutzel[e], Rachel Coy[e], Marisa Censani[f]

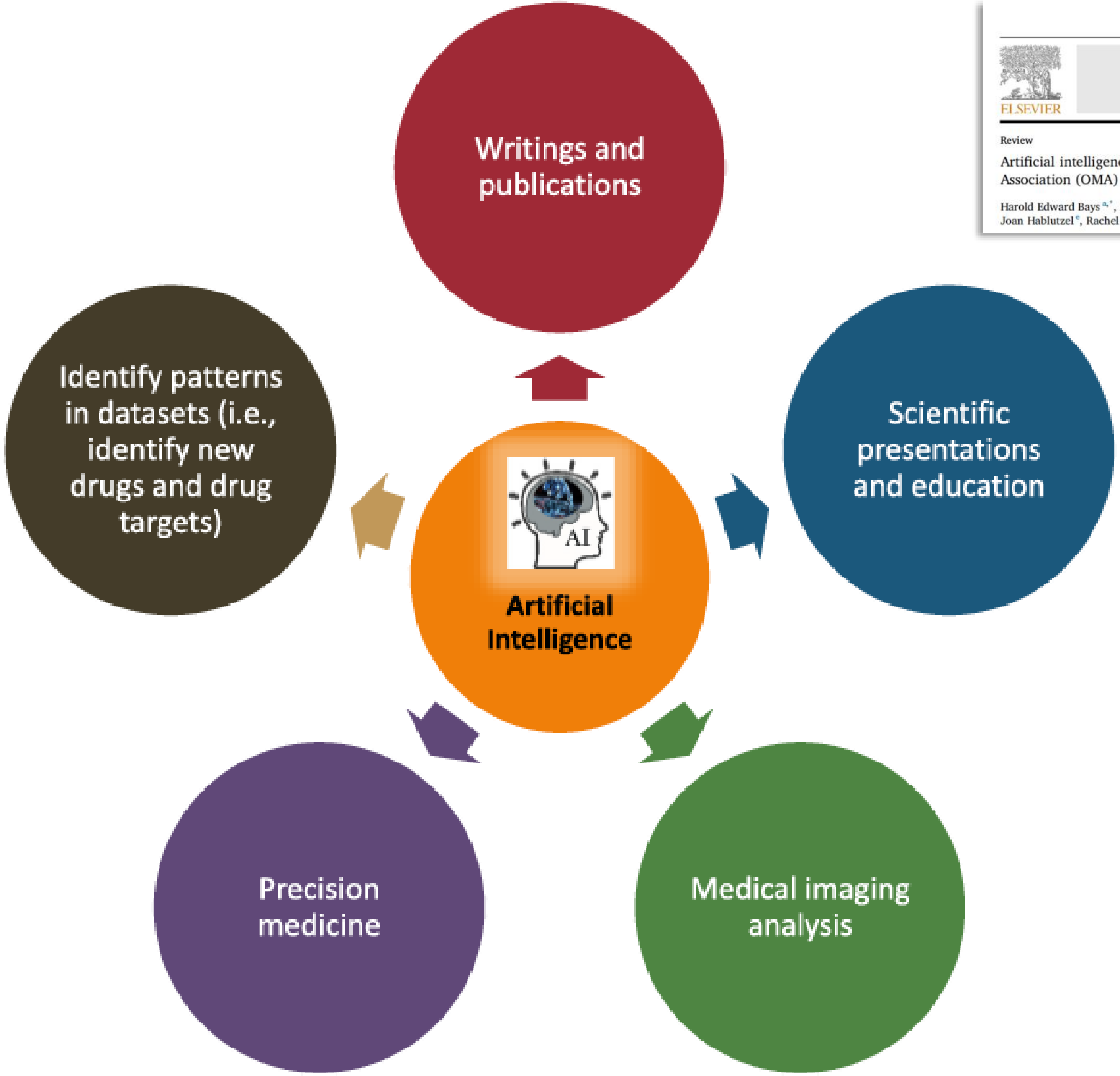


Fig. 6. Illustrative uses of artificial intelligence in medical research.

AI, Future OR


sensors

MDPI

Review

Artificial Intelligence Surgery: How Do We Get to Autonomous Actions in Surgery?

Andrew A. Gumbs [1,*], Isabella Frigerio [2], Gaya Spolverato [3], Roland Croner [4], Alfredo Illanes [5], Elie Chouillard [1] and Eyad Elyan [6]

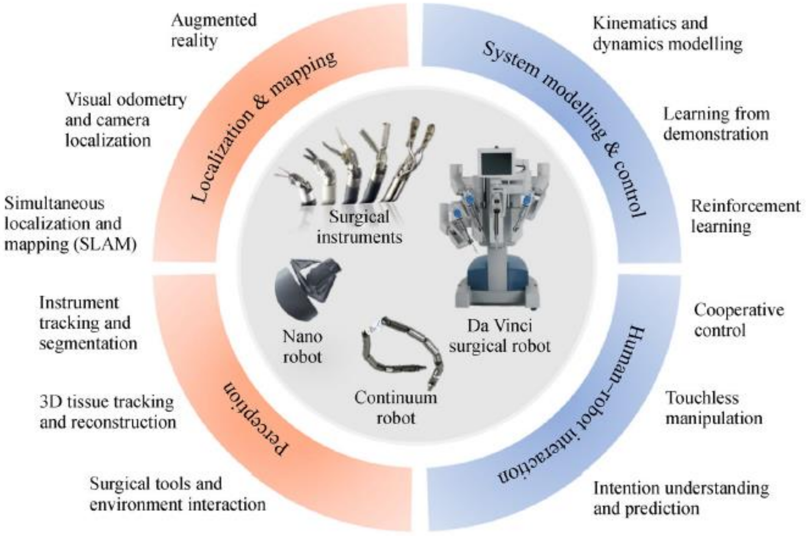

Front. Med.
https://doi.org/10.1007/s11684-020-0770-0

REVIEW

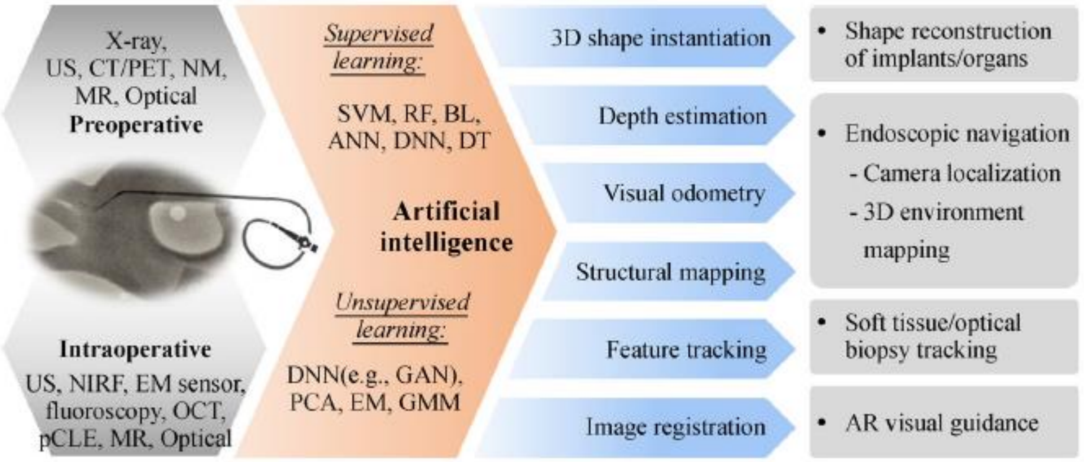
Application of artificial intelligence in surgery

Xiao-Yun Zhou (✉)[1], Yao Guo[1], Mali Shen[1], Guang-Zhong Yang[2]

- AI-assisted robotic systems
- Real-time image analysis and tissue recognition
- Augmented reality overlays



- Advantages:
  - Increased precision
  - Reduced surgeon fatigue



Future

Preoperative planning

- More public available large-scale datasets for training DCNNs
- Federated learning, meta-learning and explainable AI
- Early detection and diagnosis based on multimodal information

Intraoperative guidance

- Shift from static image displays to show dynamic organ function
- Advanced AR and VR technologies for surgical training and teaching
- Remote surgical cooperation between multidisciplinary teams

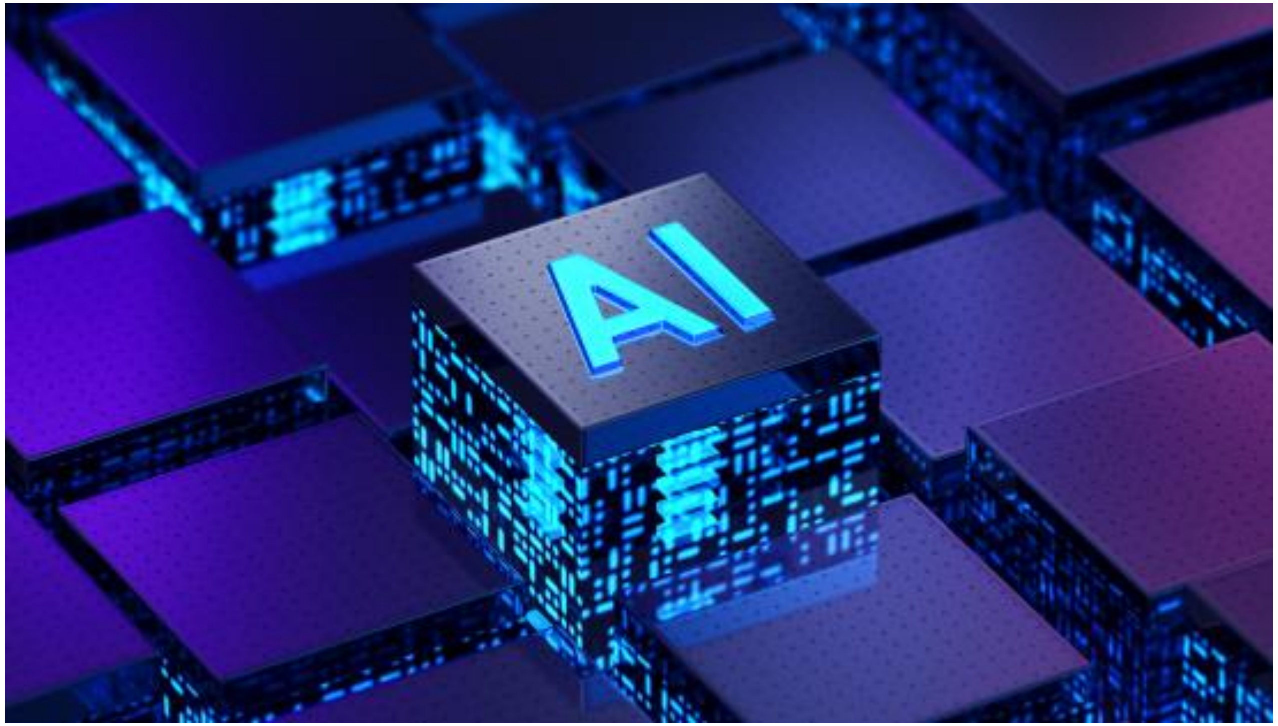
Surgical robotic

- More versatile, lighter, and cheaper robots
- Increased level of robotic autonomy with LfD and RL
- Nanorobot for diagnosis and drug delivery

Ethical and legal issues

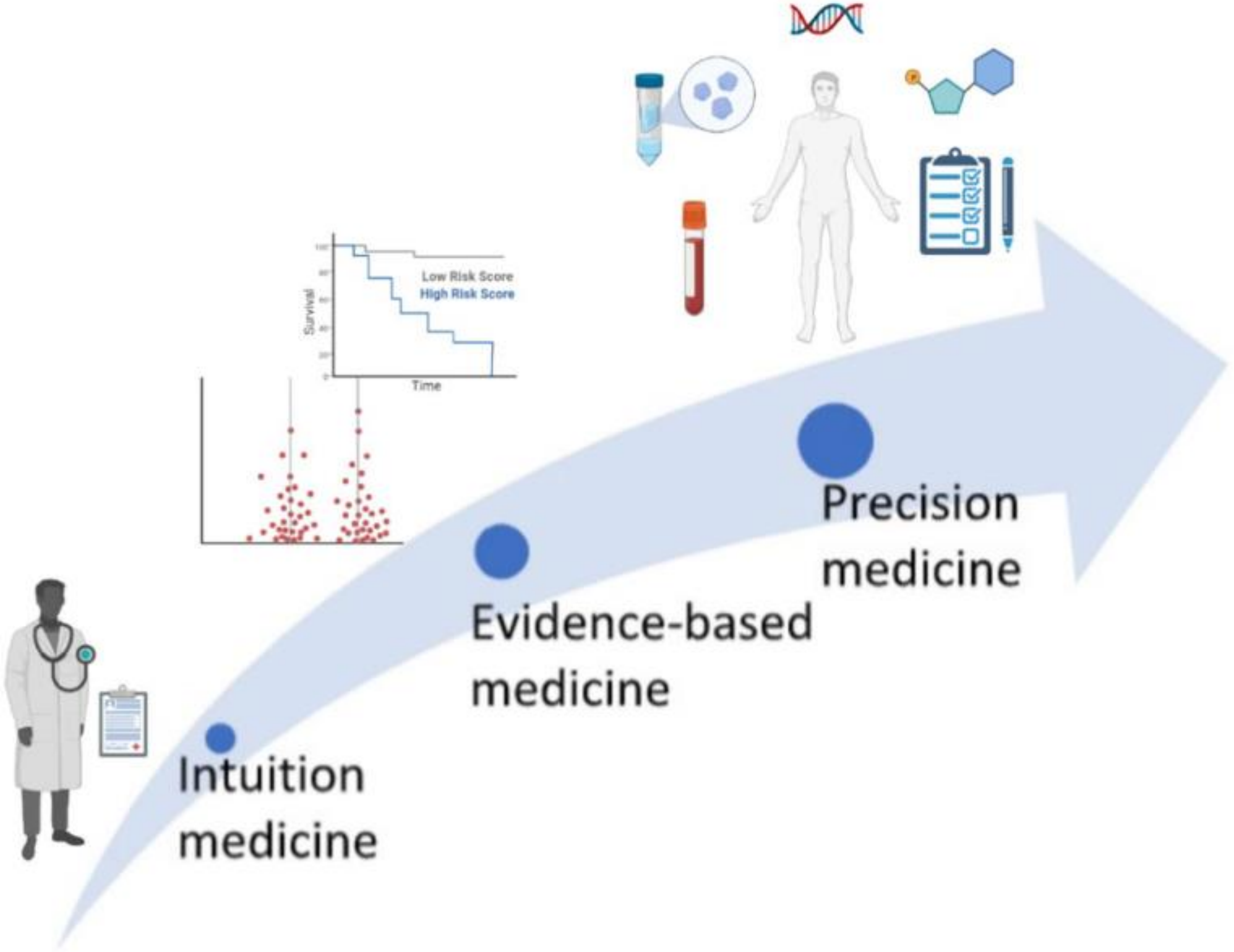
- Protect the privacy of patients' data
- Cybercrime—supportive system when failures happen in AI
- Ethics—trust between patients and AI systems

The Next Era in Bariatric Surgery:

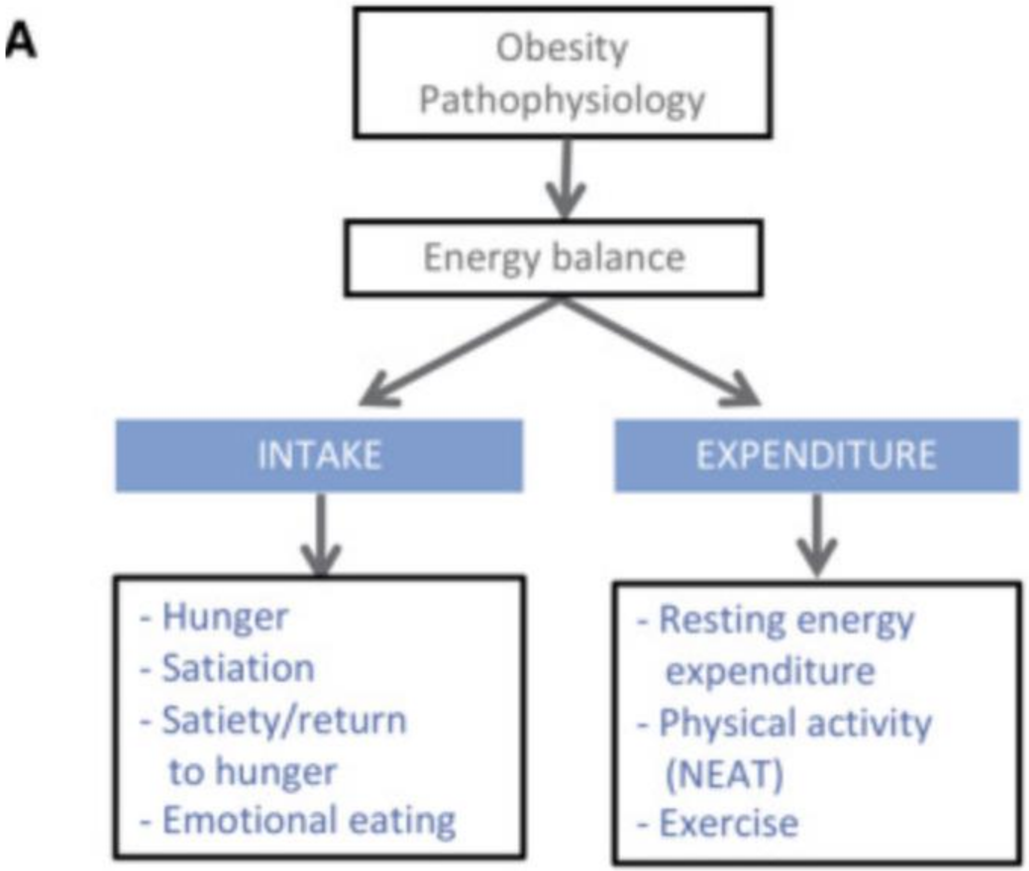


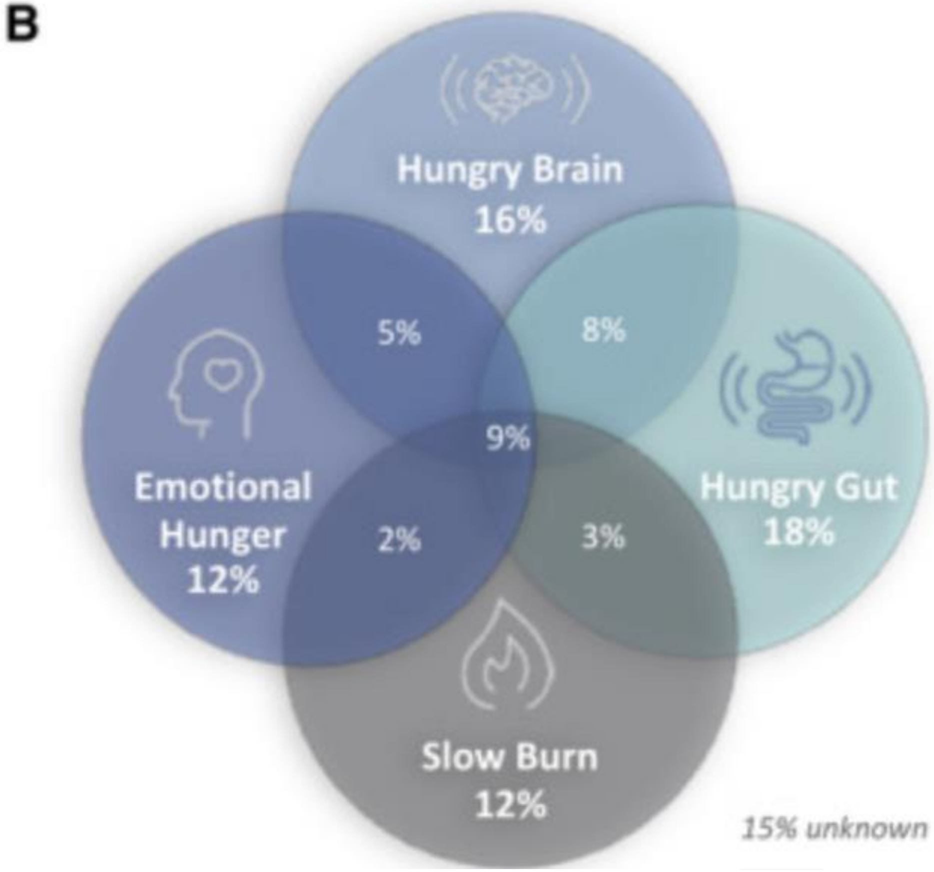
4. Phenotype-driven care

- The term “morbid obesity” will disappear. **We will classify patients not by BMI, but by metabolic subtype, visceral adiposity, insulin resistance, and hepatic phenotype**.
- AI-driven decision support systems will guide procedure selection, not surgeon preference.


Low Risk Score
High Risk Score
Survival
Time
Intuition medicine
Evidence-based medicine
Precision medicine

Precision Medicine





Acosta, A., et al.. (2021), Selection of Antiobesity Medications Based on Phenotypes Enhances Weight Loss: A Pragmatic Trial in an Obesity Clinic. Obesity, 29: 662-671

Future Prospects of AI in MBS

scientific reports

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International expert consensus on the current status and future prospects of artificial intelligence in metabolic and bariatric surgery

Mohammad Kermansaravi[1], Sonja Chiappetta[2], Shahab Shahabi Shahmiri[1], Julian Varas[3], Chetan Parmar[4], Yung Lee[5], Jerry T. Dang[6], Asim Shabbir[7], Daniel Hashimoto[8], Amir Hossein Davarpanah Jazi[1], Ozanan R. Meireles[9], Edo Aarts[10], Hazem Almomani[11], Aayad Alqahtani[12], Ali Aminian[13], Estuardo Behrens[14], Dieter Birk[15], Felipe J. Cantu[16], Ricardo V. Cohen[17], Maurizio De Luca[18], Nicola Di Lorenzo[19], Bruno Dillemans[20], Mohamad Hayssam ElFawal[21], Daniel Moritz Felsenreich[22], Michel Gagner[23], Hector Gabriel Galvan[24], Carlos Galvani[25], Khaled Gawdat[26], Omar M. Ghanem[27], Ashraf Haddad[28], Jaques Himpens[29], Kazunori Kasama[30], Radwan Kassir[31], Mousa Khoursheed[32], Haris Khwaja[33], Lilian Kow[34], Panagiotis Lainas[35], Muffazal Lakdawala[36], Rafael Luengas Tello[37], Kamal Mahawar[38], Caetano Marchesini[39], Mario A. Masrur[40], Claudia Meza[41], Mario Musella[42], Abdelrahman Nimeri[43], Patrick Noel[44], Mariano Palermo[45], Abdolreza Pazouki[1], Jaime Ponce[46], Gerhard Prager[22], César David Quiróz-Guadarrama[47], Karl P. Rheinwalt[48], Jose G. Rodriguez[49], Alan A. Saber[50], Paulina Salminen[51], Scott A. Shikora[43], Erik Stenberg[52], Christine K. Stier[53], Michel Suter[54], Samuel Szomstein[55], Halit Eren Taskin[56], Ramon Vilallonga[57], Ala Wafa[58], Wah Yang[59], Ricardo Zorron[60], Antonio Torres[61], Matthew Kroh[62] & Natan Zundel[63]

Challenges of AI Integration

- Data privacy and security
- Algorithm bias and fairness
- Interpretability and trust in AI
- Integration into surgical workflow

Ethical Considerations & The Future

- Ethics are Paramount
    - Ethical use is crucial, requiring adherence to guidelines, inclusion in patient consent, and clear accountability for AI-driven decisions
- Future Directions
    - The future includes mandatory AI education in surgical curricula, advanced AI-driven robotics, and personalized interventions through genomic data integration

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China's Mainland

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